



Estimating Power Loads from Partial Appliance States

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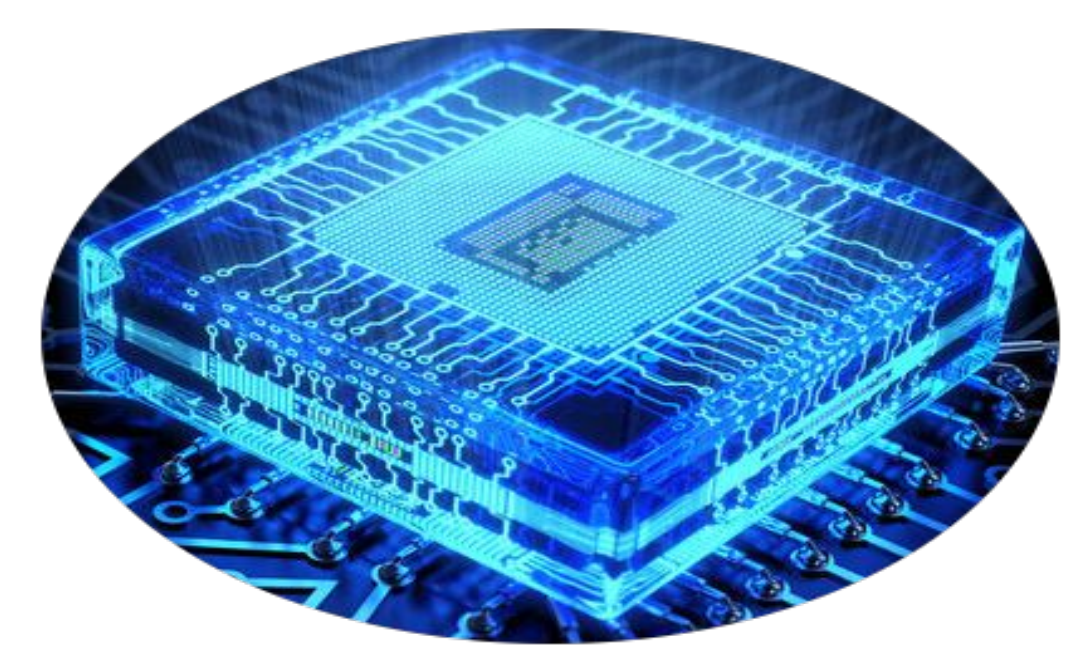
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Estimating Power Loads from Partial Appliance States

Nicolas Roux (nicolas.roux@inria.fr), Baptiste Vrigneau, Olivier Sentieys

General scope

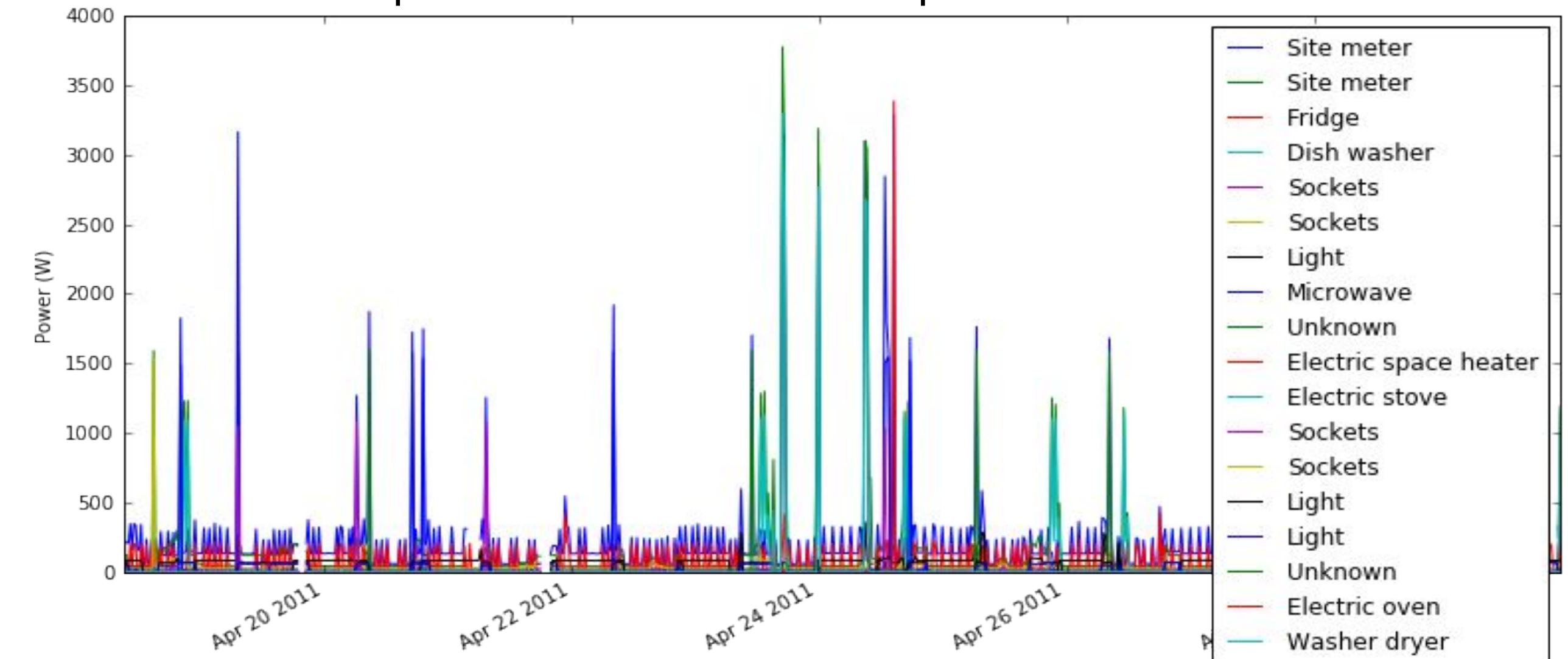
Knowing the plug-level power consumption of each appliance in a building can lead to significant savings in energy consumption, as well as giving a deep insight of a building power consumption. A critical information is the knowledge of the characteristic power consumptions of an appliance. The problem can be stated as an optimization problem as follows :

$$\min_{w_{i,j}} \|x_{tot}(t) - \sum_{i=1}^N \sum_{j=1}^{M_i} w_{i,j} \times s_{i,j}(t)\|_d \quad (1)$$

- $w_{i,j}$ the steady state power value j for appliance i
- x_{tot} the main aggregated power of all appliances
- N the total number of monitored appliances
- M_i the states count for appliance i
- $s_{i,j}$ a boolean which indicates if appliance i is in state j
- d a given norm.

Non-Intrusive Load Monitoring (NILM)

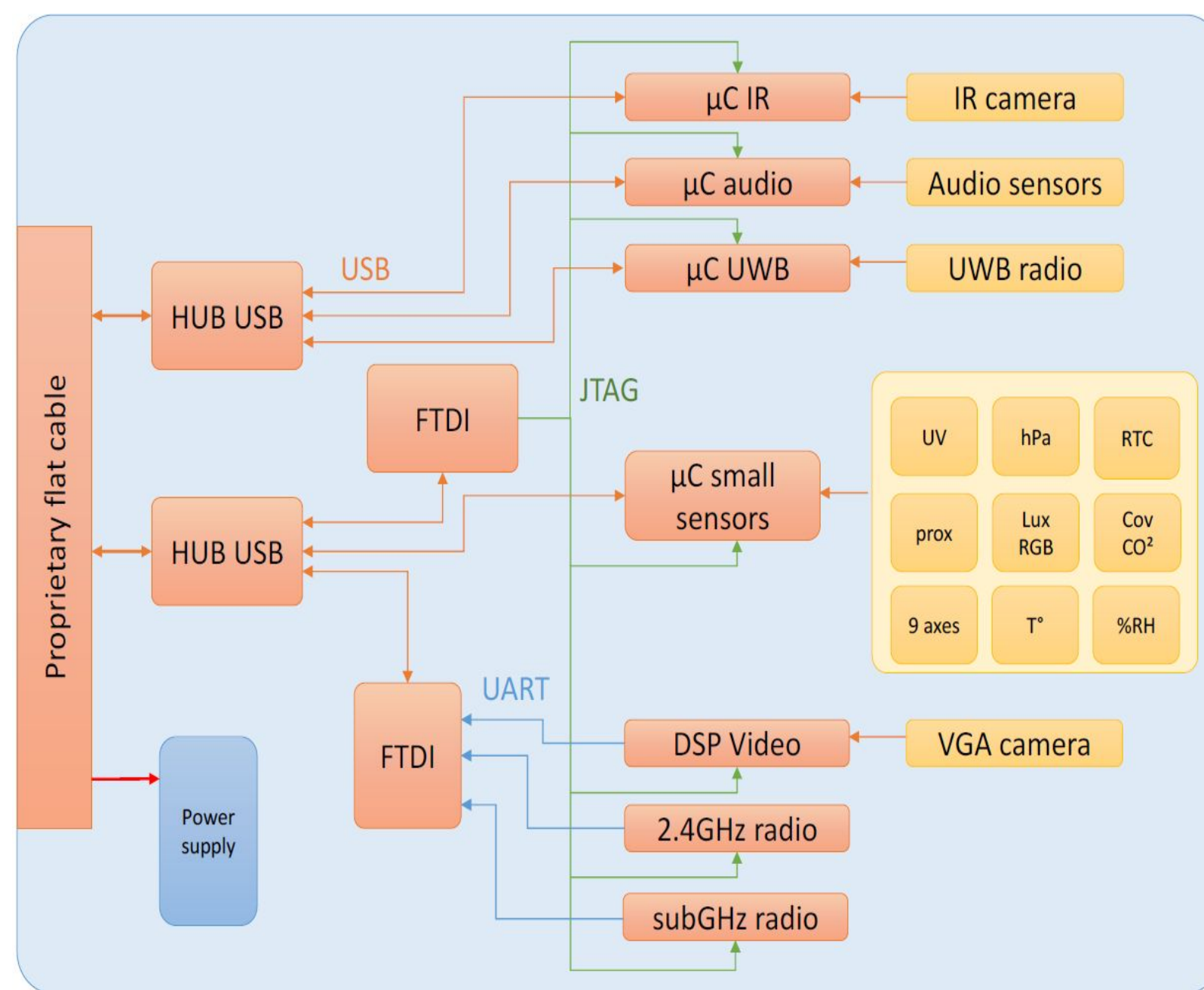
An example of NILM on the REDD public dataset House 1



Main power of a building is disaggregated to isolate single appliance power consumptions. This ensures a better understanding of the energy consumption in a building. Most of the current NILM methods have an *a priori* knowledge of the individual signatures or are trained on single appliances.

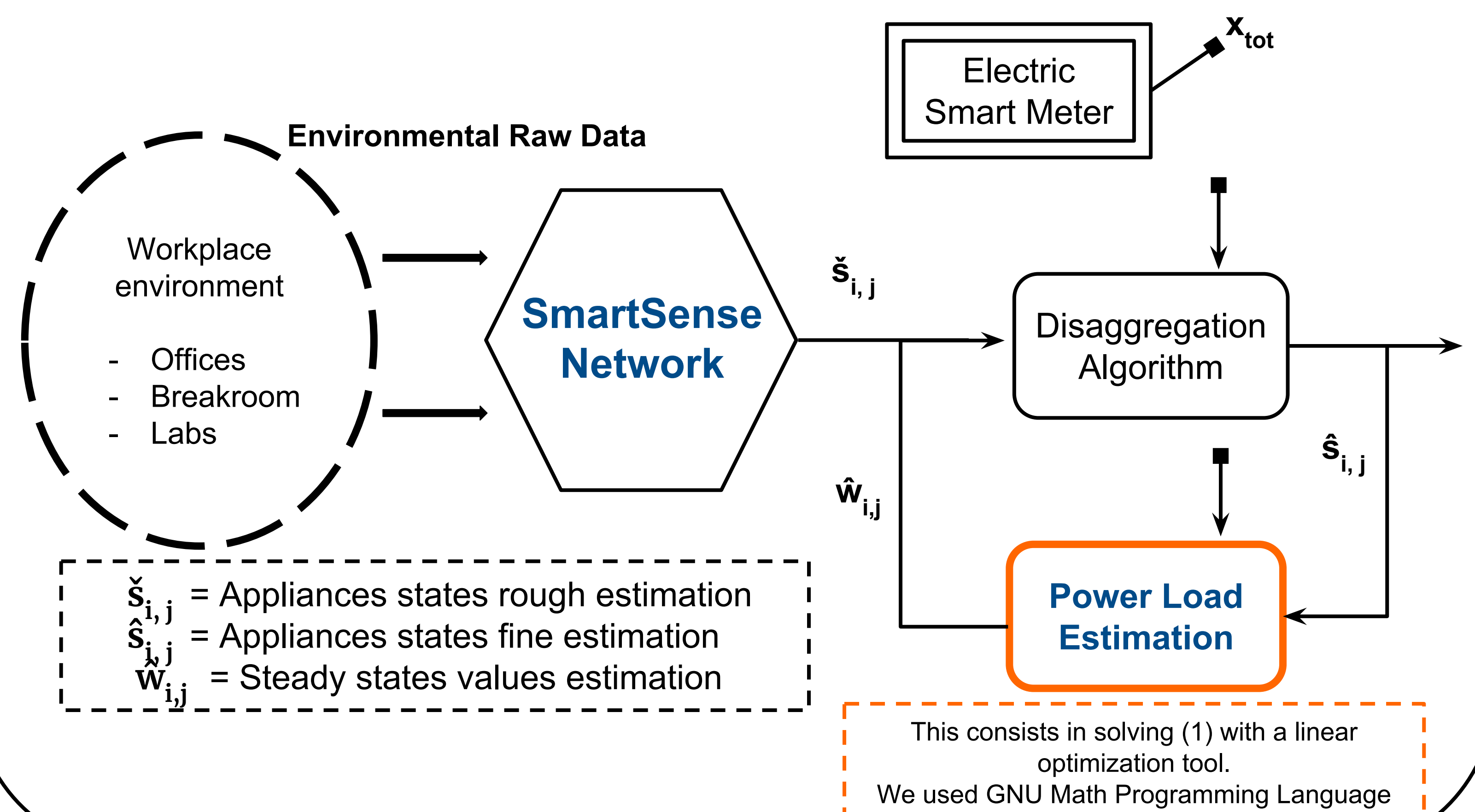
SmartSense

- We believe that additional info can help in improving disaggregation algorithms
- Basic computations made directly on sensor node
- Ensures low network usage and user privacy
- Environment is an electronic lab
- 156 nodes are deployed
- More info and data download at smartsense.inria.fr



Block-diagram of a SmartSense Node

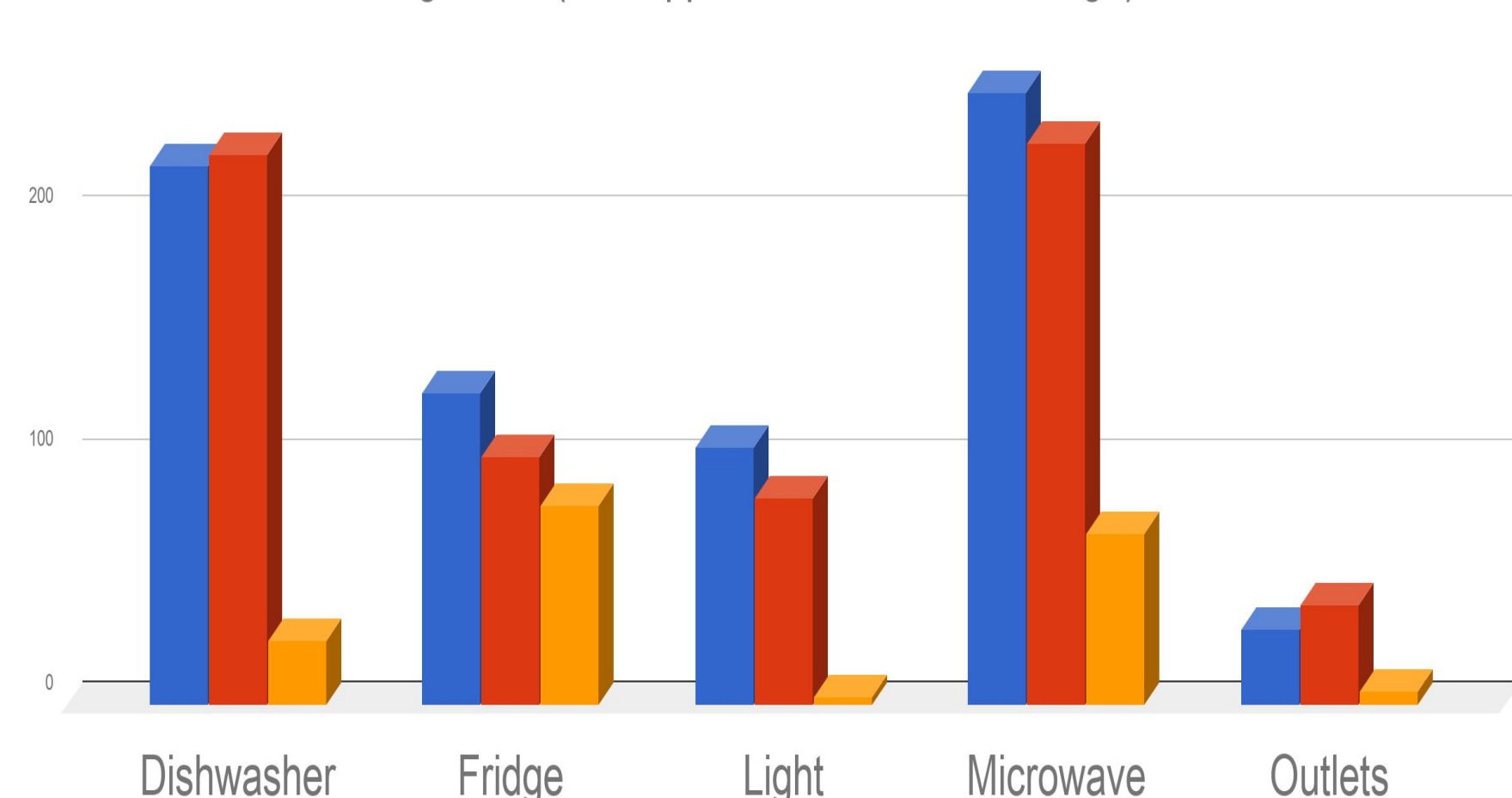
Dataflow



Comparison with "blind" algorithms

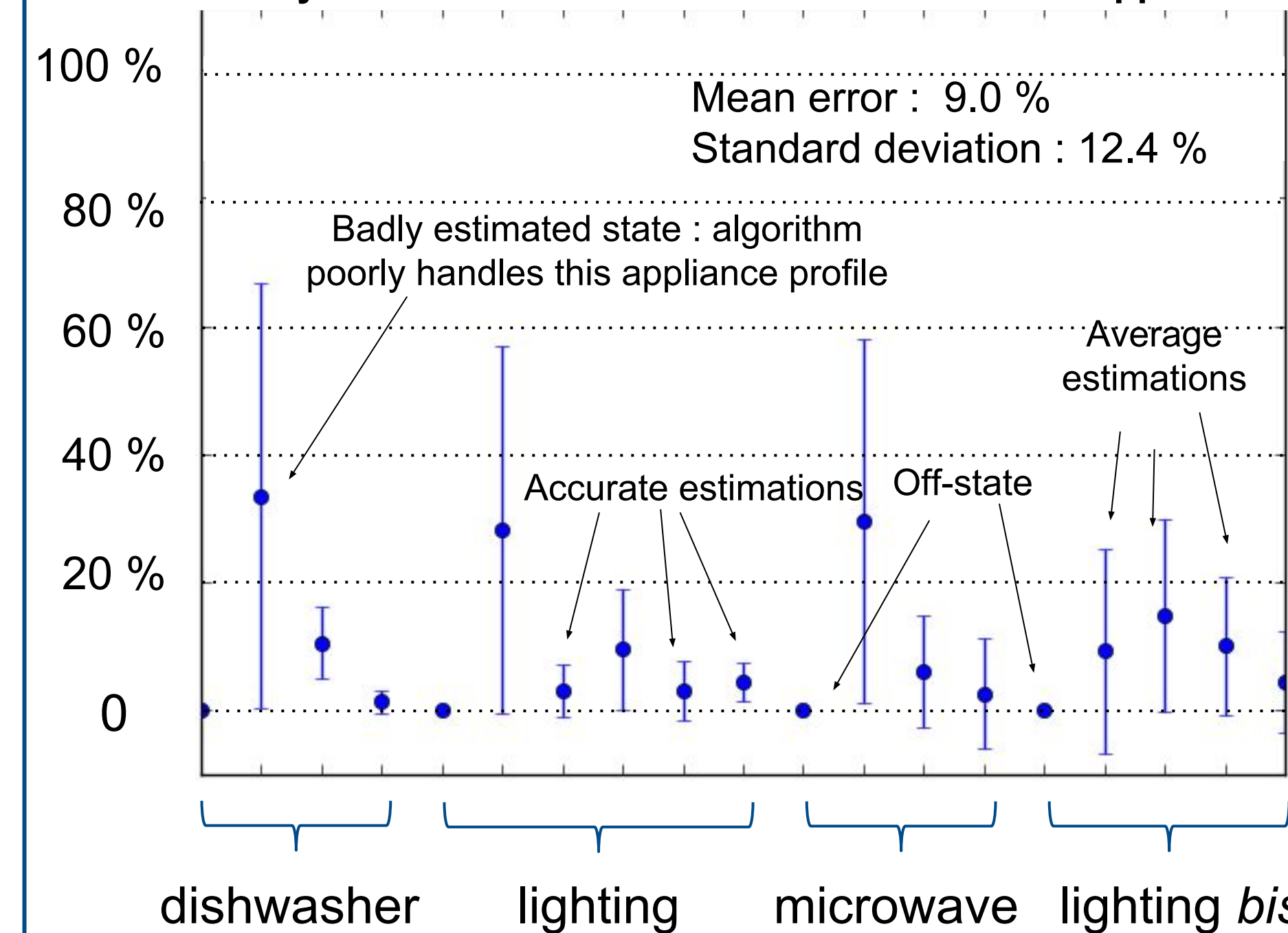
RMS error between predicted and true power for REDD 1 appliances

CO FHM Our algorithm (with appliances states knowledge)

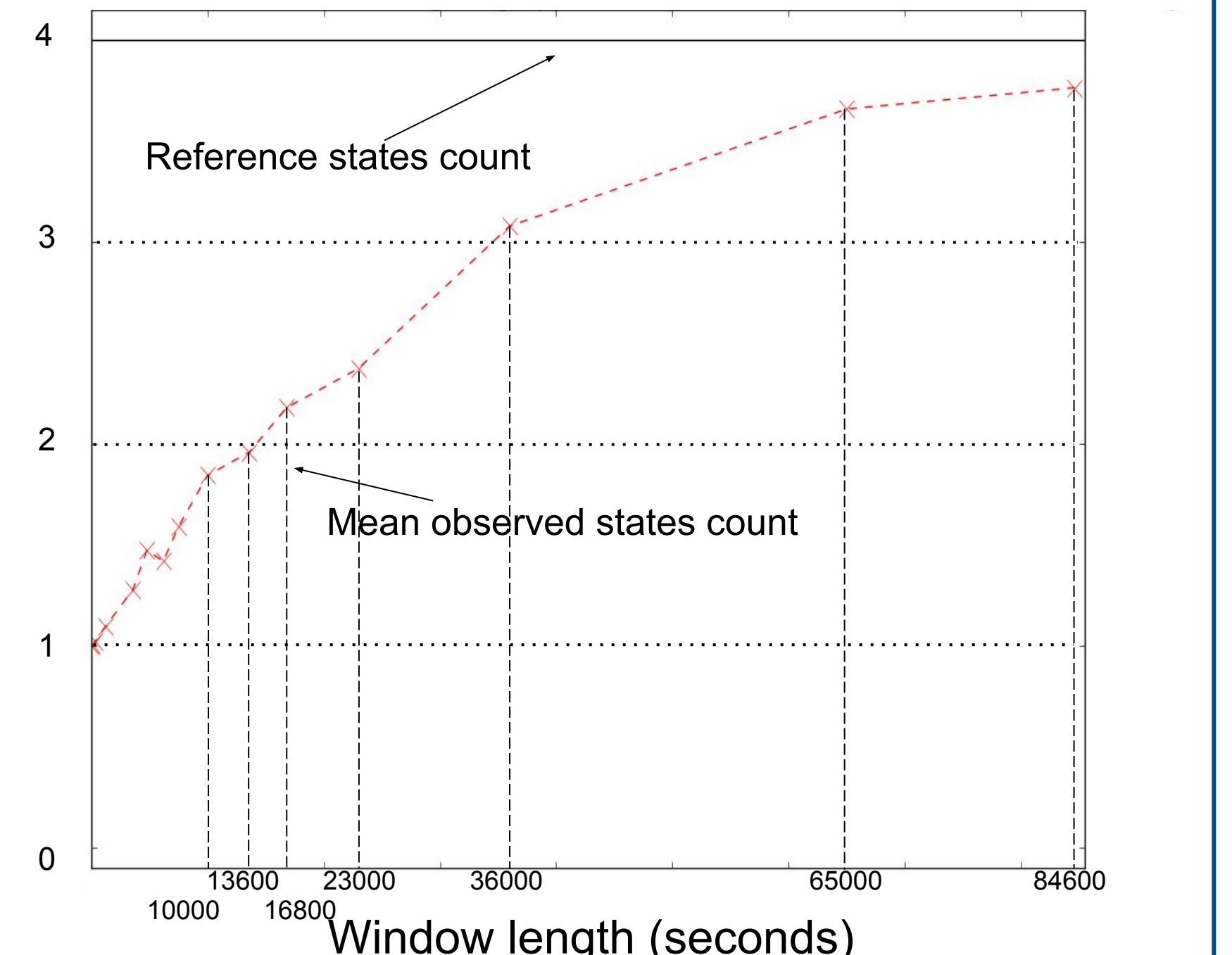


States detection and estimation accuracy

Steady states values errorbars for various REDD appliances



Lighting circuit appliance states count



Conclusion

- An estimation algorithm based on environmental sensing has been proposed.
- SmartSense, a sensor network with a wide range of sensors is introduced.
- Promising results are displayed in terms of complexity and prediction error, but the algorithm showed significant variations according to the nature of the appliance power time series.

Future work

- Smartsense deployment and data collection are imminent.
- Smartsense is expected to yield accurate environmental data but inaccurate appliance states matrix.
- Next challenges to address are the algorithm robustness to this kind of errors, and association between NILM algorithms and environmental data instead of electrical data.

